Appendix C
Quantifying Uncertainty in Climate Change Analyses

This appendix discusses the sources of uncertainty in climate change analyses and methods for addressing and quantifying uncertainty in planning studies. Probabilistic methods and scenario planning are two common methods for incorporating uncertainty into planning analyses.

Uncertainty is a feature of any planning study, whether climate change is explicitly included or not. Accounting for and disclosing uncertainty is an established component of good planning practices. In water resources planning this has traditionally included uncertainties associated with natural climate and hydrologic variability, future population and economic conditions, and future technological advances and social trends. Climate change involves added uncertainties associated with future GHG emissions conditions and the hydroclimatic response to current and future emissions as projected by numerical models. This appendix describes the sources of climate change-related uncertainty and methods for quantifying uncertainty in planning.

Types of Uncertainty in Planning

Traditional Water Resources Planning Uncertainties

Uncertainty can be a significant part of any planning study that attempts to project future conditions that are subject to random processes using tools and understanding that are imperfect. In water resources planning, traditional sources of uncertainty have included natural hydroclimate variability, imprecision in measured model input parameters, model numerical error and inaccuracies, demographic projections, technological advances and performance, and human operational decision making.

Natural hydroclimate variability is defined here as the seasonal and yearly variations in climate (precipitation and temperature) and streamflow that has been observed in historical records. This variability includes the occurrence of droughts and floods. In water resources planning, the anticipated availability of water supply, for example, is often quantified using historical records or subsets of the available record. The assumption that a limited snapshot of the past is adequate for projecting the full range of potential future conditions is clearly imperfect and therefore introduces uncertainty in the projections.

Uncertainty is also introduced to planning studies through the use of data that are inherently imperfect due to inaccuracies and/or imprecision in measurement. For example, water quality modeling studies can be particularly sensitive to error in laboratory or field measurements upon which model parameterization and calibration are based. These sensitivities lead to uncertainty in projections. Similarly, uncertainties may be introduced in hydrologic studies through the use of imperfect stage-volume or stage-flow relationships. These forms of uncertainty are generally unavoidable and may or may not warrant explicit consideration in a planning study.

Process-based numerical models are typically based on simplified mathematical representations of complex natural or anthropogenic processes. As such, they are never completely accurate and their projections of the future are not certain. For example, a watershed hydrologic model might be constructed as a series of lumped-parameter “buckets” to represent the complex surface and sub-surface physical systems. This is a simplification of the real system and many potentially important processes are neglected. Consequently, simulations of runoff response to rainfall will be uncertain, particularly for conditions that fall outside the range of typical values seen in the past. This type of uncertainty can be reduced, but not eliminated, through calibration and/or verification exercises. Additionally, an element of uncertainty can be introduced in modeling studies due to numerical error: the error associated with the numerical approximations of underlying fundamental mathematical equations. This error, and consequently the resulting uncertainty, can often be reduced through model input parameter manipulations given appropriate user expertise.

Water resources planning studies often require projections of social parameters and demographics. For example, water demand projections typically rely on population projections. Demand modeling may also include projections of economic parameters, consumptive patterns, and land use change. Clearly uncertainty exists in all of these projections of the future and must be acknowledged in a planning study.

Technology changes with time. Uncertainty over how technology will advance in the future or how existing technology will perform in the future can play a significant role in water resources planning studies. For example, water quality planning studies often assume a certain level of treatment for wastewater treatment plant effluent entering a water body. If treatment technologies improve over time, water quality could be significantly impacted.

Finally, uncertainty associated with human operational decision making on a day-to-day basis can be significant in some planning studies. For example, reservoir releases may be managed based on a variety of objective and subjective criteria. This makes it challenging to model such dynamics and adds uncertainty to estimates of future reservoir conditions.

Climate Change Uncertainties

In the science of climate change, there are uncertainties associated with the climate models themselves (sometimes called epistemic uncertainty), and uncertainties associated with how the planet will respond to future conditions (sometimes called aleatory uncertainty or variability). Both kinds of uncertainty are relevant for regional water plan decision making.

With respect to the former, upwards of 20 different general circulation models (GCMs), each from different modeling centers located around the world, are widely accepted and used in climate change studies. Each of these has multiple versions based on varying input assumptions. Differences in regional downscaling techniques applied to each of these models also add to the volume of climate model projection information available for any given location. The fact that such volume exists, representing a range of projection values, for the same projected parameter (e.g., temperature or precipitation at a given location and time horizon) is indicative of the large epistemic uncertainty in GCM projections. This uncertainty arises due to differences in both model structure (i.e., underlying mathematical equations) and input assumptions (e.g., greenhouse gas emissions or cloud cover dynamics). There is simply not enough knowledge to arrive at a consensus. We can surmise that this type of uncertainty will be reduced over time as the climate change science advances.

Aleatory uncertainty in climate change studies is attributable to the randomness of many of the critical components of the system under study and is thus not reducible. In climate change studies, the "system" starts with the global climate system. There is large uncertainty in how the global climate will respond to the accumulation of greenhouse gases in the atmosphere. There is particular uncertainty with respect to precipitation impacts and annual and seasonal variability that is effectively random. In other words, for the purposes of this document, this type of uncertainty is attributable to the unpredictability of the planet's natural system response to greenhouse gas accumulation.

Techniques for Addressing Uncertainty in Water Resources Planning Studies (With or Without Climate Change)

Addressing uncertainty, either quantitively or qualitatively, in water resources planning studies aids in the decision making process. For example, a planner may make decisions based on a worst case scenario quantified as part of uncertainty analyses. Similarly, a "margin of safety" might be implemented based on knowledge of the uncertainty in model projections. Given the significant additional uncertainty associated with climate change, addressing uncertainty in water resources planning studies is even more important now than it was in the past.

There are several techniques for incorporating uncertainty into the regional water planning process, with two categories of techniques that appear particularly well-suited for quantifying climate change uncertainty:

- **Probabilistic Methods**. These methods involve defining specific input variables in terms of probability functions. Traditionally, in water resources planning studies, probability distributions might be used to represent parameters that vary randomly in nature (or are effectively random due to the complexity of the process), such as wildlife bacterial loadings to a stream or climate fluctuations on a short time scale (e.g., daily). Additionally, probability distributions might be used to quantify a model input parameter whose value is unknown but for which a realistic range of potential values can be constructed by expert opinion. In climate change studies, this approach can be extended to address the uncertainties associated with climate change projections and capture the variability of available projections. This method can be applied at different stages of the plan development. It can be applied at the earliest stages to define temperature, precipitation and sea level rise data (described in Sections 2 and 5), and can also be applied to assess climate change impacts (described in Sections 5 and 6). The performance of a climate change strategy or group of strategies is measured in terms of joint probability functions based on the input distributions. The result of this analysis can be viewed as an overall assessment of risk and is useful for decision making.

- **Scenario Planning**. This method is widely used and simple to understand. First, several plausible scenarios of potential future conditions are defined. Then projects within a regional water plan are evaluated under these different scenarios to determine the most robust strategies.

A general description of each of these two categories of techniques is presented in the sections below. Information is provided on the data requirements and the steps necessary to complete each method. The relative strengths and limitations of incorporating each method into a regional water planning process are presented. Relevant example applications from the literature are provided. A general reference on planning methods that can be used in climate change analysis can be found in the Water Utility Climate Alliance's white paper "Decision Support Planning Methods: Incorporating Climate Change Uncertainties into Water Planning" (WUCA 2010).

Probabilistic Methods

Probabilistic models provide a range of output, characterized by probabilities of occurrence, rather than the single projections provided by deterministic models. They require key inputs to be provided either as a range of possible discrete values or as continuous probability distribution functions, rather than as single values. Generally, output probabilities can be thought of as the "risk" of achieving a certain threshold. For example, probabilistic models could be used to quantify the risk of a water supply shortfall in a given planning horizon given past observed hydrologic conditions. This type of information can be very valuable to any decision making process.

As described in Section 5.1, combining GCM model results available in the CMIP3 dataset within a probabilistic framework, in which the projection of each GCM is given equal probability, is one method for addressing climate model uncertainty (Brown 2011). However, it is important to realize that probability distributions fit to these datasets do not strictly represent probabilities of occurrence. The data are model projections, not real observations, and (as discussed above) are subject to their own large uncertainties. Rather, the probabilities, and consequently the final planning model outcomes, represent *levels of consensus* in projective modeling (Mote et al 2011). We propose that this framework may be as useful as true risk assessment to planning decision making in the face of climate change.

The probabilistic method is prescriptive rather than adaptive—meaning once a decision is made about a strategy or group of strategies, they are fully implemented under the assumption that the strategy is the best (e.g., measured risk under a predefined threshold of acceptable risk to the decision maker) under varying future conditions. This probabilistic approach to decision making requires an explicit definition of risk tolerance. Decisions will be made based on the level of risk that different strategies represent; as such, decision makers need to be able to discriminate between different levels of risk.

> ***Climate-Related Risk****: The possibility of interaction of physically defined hazards with the exposed systems. Risk is commonly considered to be the combination of the likelihood of an event and its consequences – i.e., risk equals the probability of climate hazard occurring multiplied by the consequences a given system may experience. (Sometimes risk is defined as hazard exposure times 'vulnerability', where vulnerability is merely the sensitivity and adaptive capacity of the exposed system.)*
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> *--- United Nations Development Programme 2005*

Conducting the Probabilistic Analysis

Numerical probabilistic models often incorporate random, or "stochastic", sampling in the analysis. This approach can be either "parametric" or "non-parametric" in nature. For the former, continuous probability distribution functions (PDFs) are fit to input data, such as the GCM climate data (ensemble or individual model projections). The PDFs would then be sampled over multiple iterations within the analysis process. For the latter, the actual data would be sampled, without assuming an underlying distribution. This type of iterative "bootstrap" sampling with replacement is a common modeling approach for capturing variability and uncertainty in projections.

In any stochastic sampling scheme, the number of sampling iterations must be set to ensure that the output properly reflects the full range of input statistical characteristics. Additionally, it may be necessary to incorporate input data couplings or correlations in the sampling. For example, there may be an identified correlation between monthly mean temperature and monthly precipitation. In such a case, these two parameters cannot be sampled independently of each other but rather must be sampled in a way that retains the quantified correlations. Multiple software tools exist for both PDF curve fitting and stochastic sampling, including @RISK (Palisade Inc., www.palisade.com/risk/), Crystal Ball (Oracle, www.oracle.com), and Excel (Microsoft Inc.). All of these tools also allow for the presentation of results probabilistically, often as cumulative distribution functions (CDFs).

The probabilistic approach described above for sampling climate data must ultimately be linked with the final regional water plan analyses. In some cases, it may be possible to incorporate regional water plan calculations and/or models directly into a probabilistic analysis. For example, a simple regression model describing changes in demand as a function of climate parameters could be built directly into spreadsheet calculations that include probabilistic sampling of climate data. In other cases, particularly for more complicated regions, the final analysis must be performed as a separate step or series of separate steps. In this case, intermediate output may need to be generated that are then able to serve as input to the regional water plan analyses. These intermediate outputs would need to reflect the collective results of the stochastic sampling. For example, an extended (e.g., 1,000 years) stochastic time series dataset might be developed using the techniques described above, in order to serve as input to a time series planning model.

In line with the goal of probabilistic modeling, final output and/or performance metrics should be presented as a range of numbers with quantified probabilities of occurrence (or levels of model consensus, as described above). These final outputs should then support decision making in the regional planning process.

An example of a parametric probabilistic approach to quantifying climate change uncertainty can be found in the Seattle Puget Sound demand study described in Section 5 (Box 5-1). In this study, probability distribution functions were fitted to historical demand data and modified to reflect climate change based on quantified regression "elasticities" that isolate the relationship between demand and climate variables. Future climate conditions were quantified using an ensemble of multiple GCM projections. Monte Carlo sampling of the input distributions were used to generate output cumulative probability distribution functions (CDFs).

An example of a non-parametric probabilistic analysis to address climate change uncertainty can be found in Cox et al. 2011. In this water supply study for the City of Santa Fe (NM), output from six different GCM models were pooled for two different emission scenarios. All of the GCM data corresponded to a single future planning horizon (2050 – 2070). The combined climate data were sampled randomly as two sets of pooled discrete data, rather than fitting a continuous PDF to the data. Significant month to month correlations in temperature were identified and incorporated into the random sampling. The results of the sampling were two sets (for each of the two emission scenarios) of 1000 year synthetic timeseries of monthly precipitation and temperature data that captured a large range of GCM projection variability. These data were used to seed hydrologic models that ultimately provided performance metrics (e.g., annual surface water supply delivery) in the form of probabilistic percentile curves.

Strengths and Weaknesses of Probability Analysis

The strengths of probabilistic modeling relate to the direct handling of model uncertainties and in the presentation of risk-based results. The structure of probabilistic models allows the user to input a range of values for a given parameter, with associated confidence levels, to reflect the uncertainty surrounding the parameter. These uncertainties are then compounded in the analysis with final output reflecting the combined impact of the individual parameter uncertainties. The compounded uncertainties are presented as risk levels associated with a specific performance metric, an appealing framework for both planners and regulators.

The primary weakness of the approach is that it often requires a significantly higher level of expertise compared to deterministic modeling and may require additional analytical tools and software. Additionally, data requirements are generally greater than deterministic methods, in order to support the parameterization of probabilistic inputs.

Finally, the fact that the output of the analysis is probabilistic requires the ability to interpret probabilistic information not only by the analyst but also by decision makers. In order to facilitate the interpretation of probabilistic results by decision makers, some output simplification may be required and the use of some interpretive charts and tables will be necessary. The technical analysts need to pay particular attention in these simplification steps to still preserve the relevant uncertainty in the output and the key characteristics of it. Usually, relevant information for decision makers is presented in the shape of a distribution, or its tail ends (extreme conditions).

The use of only an average to characterize the probabilistic value of an output of interest (e.g., water supply deficit) runs the risk oversimplifying the problem and making it look deterministic, with important implications for decision making.

Scenario Planning

Scenario planning is widely used and simple to understand, and it is similar to Robust Decision Making, described in Section 7. This method fully defines several potential "futures" (i.e., scenarios). Strategies are then evaluated under these different scenarios to determine the most robust strategy. For instance, one scenario might consist of future conditions that are warmer and wetter than current conditions, while another might consist of future conditions that are much warmer and drier than current conditions. The strategies' performance is compared under all scenarios. Then each strategy can be evaluated for its performance under different climate conditions. A strategy that performs well under all scenarios would likely be preferred. Scenario analysis also provides good information for choosing "no regrets" strategies, meaning strategies that provide benefits across all scenarios of future conditions.

With this method, there typically is no quantitative assessment of probability for the selected scenarios, but in many cases a weight can be assigned to different scenarios representing the collective professional judgment about the credibility of the scenarios.

Section 5.2.2 describes how climate change scenarios can be developed using discrete climate model projections or an ensemble of climate projections.

Conducting the Scenario Planning Analysis

Scenario planning requires the planner to conduct a series of workshops with stakeholders and decision makers in addition to technical analysts. Developing the planning scenarios is typically a group exercise that takes place over a number of working sessions. Generally, the scenario definition process involves the following steps:

1. Understanding the system (e.g., watershed or region) and driving forces behind the variables of interests;
2. Identifying the key uncertain variables (e.g., future atmospheric temperature and precipitation) that define the range of unexpected future conditions that stakeholders wish to explore and ranking these variables in order to define a manageable number of scenarios;
3. Identifying the range of expected future conditions that stakeholders wish to explore;
4. Combining uncertainties to create a scenario table, and then describing these scenarios; and
5. Defining a pathway to each scenario.

The key elements of each step are described below:

1. <u>Understanding the system and driving forces</u>. Planners need to define those variables, independent of climate change, that drive the behavior of the region. For example, water demands for a region may be driven mostly by population growth and agricultural use. These driving forces are related to climate change but the climate change variables are not the emphasis of this scenario planning step. In this step of the process, brainstorming (often in interviews or stakeholder workshops) is commonly used to capture the full spectrum of driving forces before they are assessed.
2. <u>Identifying key uncertainty variables</u>. During this step of scenario planning, the key variables driving climate change uncertainty (e.g., sea level rise, temperature, or precipitation) are identified by the analysis team (experts) and presented to stakeholders. These key variables should be ranked and will be directly associated with the development of scenarios.
3. <u>Identifying the range of expected future conditions that stakeholders wish to explore</u>. Individual stakeholders may be acutely concerned about specific future conditions that could be detrimental to their interests. For instance, a salmon fisherman may be specifically concerned about extremely hot and dry future conditions that would stress salmon populations by decreasing streamflow and increasing the temperature of rivers. Alternatively, a floodplain manager maybe more concerned about future conditions that are cool and wet. Thus, the scenarios must incorporate a range of potential future conditions that meet the needs of stakeholders.
4. <u>Combining uncertainty to create scenarios</u>. Some of the literature recommends reducing the number of key variables to two, so that a 2 by 2 matrix of scenarios can be developed (WUCA 2009), which in traditional planning (including water resources planning) has proven to be adequate. This 2 by 2 matrix might consist of two scenarios for population growth (high and low) and two scenarios for land use trends (expansive development and compact development).

When climate change uncertainties are added to the analysis, another dimension is added to the matrix, significantly expanding the required analysis. In addition, it is difficult to adequately cover the range of uncertainty in climate change projections without analyzing multiple scenarios. Climate change projections typically output two important variables for water resource planning: temperature and precipitation. These two outputs vary independently, thus at least four scenarios are necessary to describe potential extreme results of climate change. A further scenario is necessary to describe a mean or median climate change scenario.

Combining variables of uncertainty in this case may be better represented by a tree than a two-dimensional matrix. Figure C-1 illustrates the difference between the 4-scenario matrix and the multiple scenario tree.

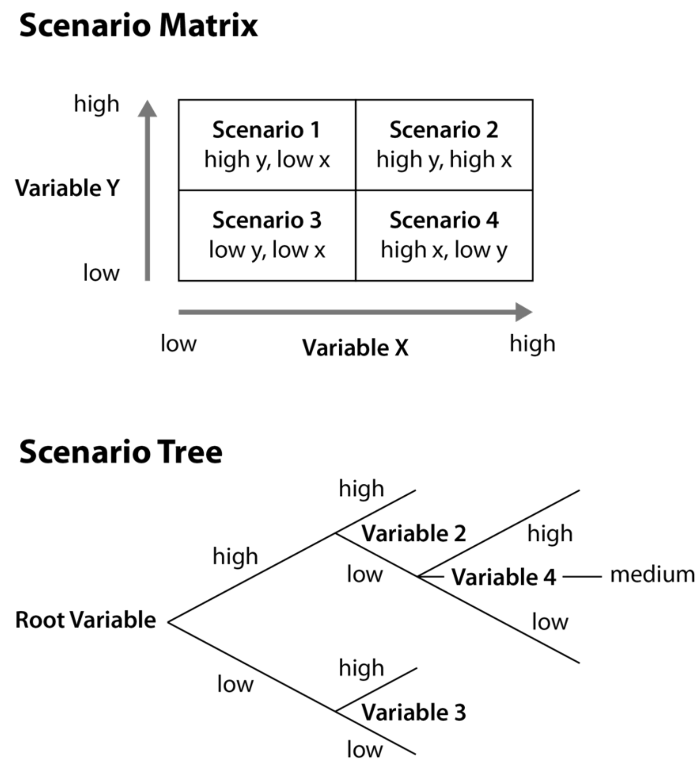

Figure C-1. Scenario Matrix vs Scenario Tree. Source: WUCA 2010.

Each branch of the tree needs to be thoroughly described by the planning group. A short document consisting of one or several paragraphs is typically written to describe each scenario, so that every decision maker is clear about them. A simple figure or table is usually insufficient to clearly describe a scenario and can result in different interpretations by different stakeholders.

5. Defining Pathways. The description of scenarios is followed by the definition of the pathway to each scenario (how the system transitions from today to the state described by the scenario, in the time frame included in the planning horizon). Defining pathways may be conducted in a workshop setting where the stakeholder group plots

independent pathways, each representing a sequence of strategies and projects, that would be necessary to realize each unique scenario based upon its specific characteristics and issues. Despite differences among the developed pathways, similarities and overlaps will occur; this commonality indicates which projects and programs would be most viable over time. This step is critical in decision making since it will provide the information necessary to define projects and strategies that can help change the outcome of the system performance under each scenario path.

6. Evaluating Alternative Plans. Once all scenarios are clearly defined, the different strategies and projects included in a regional water plan can be evaluated under each scenario. This evaluation is not a probabilistic evaluation; rather, it is a deterministic evaluation given that the uncertainty variables have been defined by a deterministic value for each scenario. That simplifies the analysis under each scenario, as compared to a probabilistic analysis. Depending on the number of scenarios, however, the overall effort of scenario planning compared to the effort in a probabilistic analysis may be similar or greater.

   The performance of alternative plans and strategies can be evaluated in two different ways under scenario planning: given a scenario, the performance metrics of the plan are better or worse compared to other plans and strategies. Alternatively, the path to arrive at a given scenario is modified after applying a set of plans and strategies, and the resulting potential future is transformed positively. In other words, the scenario itself is impacted by a strategy and the future that it describes is better than in the original scenario. These two different methods to evaluate performance are valid and will be dictated by the variables used to define the scenarios, and whether or not the analysis allows for feedback between variables and the strategies being tested.

   In most cases for regional water plans, the analysis will be more practical if strategies are analyzed in terms of the set of performance metrics under each scenario, without consideration to how a scenario could change based on the implementation of strategies. Various methodologies for performing this analysis are described in Section 5.

7. Decision Making. In the decision making step, consideration can be given to the different likelihood of the scenarios being used. In the scenario tree in Figure 7-2 (or the cells in the matrix in that figure), a weight for each tree branch can be assigned. The weight should not be confused with probability since probability implies a mathematical dimension that is not there in the simplified weight value. The weight of the scenarios can be valued to represent the professional judgment of the group in terms of the likelihood of the different scenarios. This weighted information can be then used in ranking the performance of the strategies and plans. Additional methodologies for performing this step are described in section 6.

   In the decision making step, projects and strategies are selected that work well under a range of scenarios. These projects and strategies are sometimes referred to as "no-regret solutions" or "co-benefit" solutions.

Strengths and Weaknesses of Scenario Planning

Some of the strengths of scenario planning are related to the amount of data required for the analysis, compared to the data required in the probability analysis. Given that no specific probabilities are necessary for the scenarios and that the variables of interest don't require a probabilistic output, the analysis can be conducted with less sophisticated tools.

Another significant strength of scenario planning is that the process to develop scenarios is very valuable as a learning process for stakeholders and decision makers. Stakeholders involved in the development of scenarios will learn about the key uncertain variables and better understand how uncertainties can play a role in shaping potential futures. When done correctly, scenario development is usually accompanied by some significant discussion about the system and the system's behavior to different triggers, so the learning for stakeholders and decision makers goes beyond the climate change impacts. They usually gain a greater understanding of the system structure and responses independent of climate change.

Scenario planning is useful when the management strategies and projects do not have great flexibility. For example, if the main options on the table to achieve regional objectives are related to large scale infrastructure, the phasing of that infrastructure may not be very flexible. When the actions that can be taken, or projects that can be implemented, are smaller or more flexible in nature (e.g., different levels of reservoir releases, or small scale best management practices for water quality management) adaptive management may be a stronger option.

One of the weaknesses of scenario planning is the heavy emphasis on the development of scenarios compared to the effort involved in evaluating the performance of the actual decisions under each scenario. In other words, scenario planning in some cases may fall short in the analytical elements necessary to make decisions in light of the scenarios developed. Another weakness of scenario planning, when resources are limited for it, is that the number of scenarios are reduced to just a handful. In these cases, the number of scenarios may be insufficient to adequately frame the universe of potential futures.

Combining Emissions Scenarios

A particular aspect of planning projects with climate change analysis where probabilistic methods can be combined with scenario planning is the handling of carbon emission scenarios in the technical analysis.

Several studies using GCM projections have developed ensemble GCM projections by combining projections that use different emissions scenarios (Chung et al 2009). However, some studies maintain the emission scenarios separate and avoid the ensemble averaging of them (Cox et al 2010). Combining scenarios inherently assumes that each scenario is equally likely. This can be appropriate as long as the assumption is understood by all decision makers. For planning horizons beyond 2050, planners may consider maintaining separation in the emission scenarios.